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A COMPARISON OF EMISSIONS ESTIMATED IN THE TRANSIMS APPROACH WITH THOSE ESTIMATED FROM CONTINUOUS SPEEDS AND ACCELERATIONS

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ABSTRACT

TRANSIMS is a simulation system for the analysis of transportation options in metropolitan areas. It's major functional components are: (1) a population disaggregation module, (2) a travel planning module, (3) a regional microsimulation module, and (4) an environmental module. In addition to the major functional components, it includes a strong underpining of simulation science and an analyst's tool box. The purpose of the environmental module is to translate traveler behavior into consequent air quality. The environmental module uses information from the TRANSIMS planner and the microsimulation and it supports the analyst's toolbox.

Transportation systems play a significant role in urban air quality, energy consumption and carbon-dioxide emissions. Recently, it has been found that current systems for estimating emissions of pollutants from transportation devices lead to significant inaccuracies. Most of the existing emission modules use very aggregate representations of traveler behavior and attempt to estimate emissions on typical driving cycles. However, recent data suggests that typical driving cycles produce relatively low emissions with most emissions coming from off-cycle driving, cold-starts, malfunctioning vehicles, and evaporative emissions. Furthermore, some portions of the off-cycle driving such as climbing steep grades are apt to be correlated with major meteorological features such as downslope winds. These linkages are important, but they are not systematically treated in the current modeling systems. The TRANSIMS system holds the promise of a more complete description of the role of heterogeneity in transportation in emission estimation.

The TRANSIMS micro-simulation produces second by second vehicle positions defined by 7.5 meter cell locations. An approach has been used to convert average cell populations and average transitions between cells into fine-grained distributions of speeds and accelerations. This paper describes the approach and compares the emissions that result from: (1) actual measured trajectories, and (2) the TRANSIMS approach applied to cell positions extracted from the actual trajectories. Seven different levels of congestion of freeways are examined and three different groupings of arterials were analyzed.

OVERVIEW

Transportation activities contribute to excessive ozone, carbon-monoxide, and respirable particulate matter concentrations in urban areas. The air quality community has developed a number of tools to address these problems. Emissions typically have been estimated by assuming that people use driving patterns similar to those over which the emissions of vehicles have been tested. With these formulations, estimates of vehicle miles traveled and average speeds can be used to estimate emissions. This basic formulation has been supplemented by corrections for cold starts, evaporation from fuel tanks, and super-emitting vehicles. Recently, it has been found that current systems for estimating emissions of pollutants from transportation devices lead to significant inaccuracies [1]. One possible contributor to the inaccuracies results from deviations from the standard driving cycles that produce dramatically increased emissions [2]. Of particular concern is the effect of slopes because slopes also influence the local meteorology. When these inaccuracies are coupled to air quality models and limited meteorological data, it is difficult to tell whether the most appropriate path is being taken to achieve air quality goals [3].

The TRansportation ANalysis and SIMulation System (TRANSIMS) is being developed to address this problem as well as many other transportation analysis challenges. TRANSIMS is one part of the multi-track Travel Model Improvement Program sponsored by the U. S. Department of Transportation, the Environmental Protection Agency, and Department of Energy. Los Alamos National Laboratory is leading this major effort to develop new, integrated transportation and air quality forecasting procedures necessary to satisfy the Intermodal Surface Transportation Efficiency Act and the Clean Air Act and its amendments.

TRANSIMS is a set of integrated analytical and simulation models and supporting data bases. The TRANSIMS methods deal with individual behavioral units and proceed through several steps to estimate travel. TRANSIMS predicts trips for individual households, residents and vehicles rather than for zonal aggregations of households. TRANSIMS also predicts the movement of individual freight loads. A regional microsimulation executes the generated trips on the transportation network, modeling the individual vehicle interactions and predicting the transportation system performance.

The purpose of the TRANSIMS environmental module is to translate traveler behavior into consequent air quality, energy consumption, and carbon dioxide emissions. There are four major tasks required to translate traveler behavior into environmental consequences: (1) estimate the emissions, (2) describe the atmospheric conditions into which the contaminants are emitted, (3) describe the local transport and dispersion, and (4) describe the chemical reactions that occur during transport and dispersion of the contaminants.

The choice of components in the TRANSIMS approach is driven by the goal of representing those details that may influence the answer of the question being asked. In the context of travel the focus is on the individual traveler. In a same vein, the atmospheric model is chosen to be one that uses a relatively complete description of the physics of atmospheric circulation and includes an explicit treatment of the role of turbulence. The dispersion model is chosen to be a Monte-Carlo kernel model that can treat the effects of wind-shear, terrain flows and terrain-induced turbulence. The photochemical model is an airshed model.

METHODOLOGY

The TRANSIMS architecture includes four major elements: (1) a household and commercial activity disaggregation module, (2) an intermodal route planner, (3) a travel microsimulation module, and (4) an environmental module. The disaggregation module uses census and survey data to construct a regional synthetic population. In the future, it will also estimate travel related activities for each member of the synthetic population. Currently, travel activities are inferred from origin and destination matrices developed by regional planning authorities. The intermodal planner produces planned travel link by link and mode by mode on the travel network. The microsimulation module executes the planned travel over the urban area. The TRANSIMS environmental module is composed of a system of environmental modules that can describe both the average conditions and the fluctuations about the averages.

Input for the system will consist of surface characteristics, large-scale meteorology, terrain, traveler behavior, and vehicle characteristics. Terrain and surface characteristics for current conditions are available for US cities. For future applications, estimates will have to be made of the changes expected from the current conditions. The required large-scale meteorology is available through airport radio balloon soundings or through meteorological analyses done by the National Meteorological Center.

Household and Commercial Activity Disaggregation Module

The disaggregation module includes two components: (1) a synthetic population submodule and (2) an activity demand submodule. The synthetic population is developed from the Census Standard Tape File 3 (STF-3) and the Public Use Microdata Sample (PUMS). The PUMS has all the desired attributes of the population but it represents a sample from a much larger population than desired while the STF-3 represents a much smaller population, but it doesn't provide all the information of interest. A statistical technique called iterative proportional fitting is used to estimate the desired data at the census tract or block group level based on the PUMS correlations. The actual synthetic population is randomly drawn from the multi-way tables produced by iterative proportional fitting.

The activity demand module is not yet developed. In the interim, a module that uses the metropolitan planning organization's estimated origin and destination tables to produce synthetic activities is being used.

The Intermodal Route Planner

The planner generates routes for each load from the activity-based travel demand. A load is a traveler or a commodity. A trip plan is a sequence of modes, routes and planned departure and arrival times at the origin, destination(s), and mode changing facilities to move the load to its activity locations. We assume that travel demand derives from a load's desire or need to perform activities. The household and commercial activity disaggregration module provides the planner with disaggregated activity demand and travel behavior. The planner assigns activities, modes, and routes to individual loads in the form of trip plans. The individual trip plans are input to the travel microsimulation for its analysis.

Trip plan selection is related directly to a load's desire to satisfy individual (or in the case of freight, corporate) goals. Goals measure a trip plan's acceptability and depend on the load's socioeconomic attributes and trip purpose. Typical goals include cost, time, and distance minimization, and safety and security maximization. The load's objective is to minimize the deviations from these goals.

The travel demand problem is formulated as a mathematical program based on a multi-goal objective function. The Planner's solution method has four phases: (1) trip generation, (2) goal measurement, (3) preference adjustment, and (4) trip plan superposition. In the first three phases, the individual's travel behavior preferences such as departure time or origin-destination directness, are adjusted iteratively to satisfy the travel goals. After every load has a feasible trip plan, the fourth phase superimposes all trip plans on one another in space and time. The network characteristics are then updated based upon the projected interaction of all trips and steps (1) through (4) are repeated.

Travel Microsimulation

The Travel Microsimulation module mimics the movement and interactions of travelers throughout a metropolitan region's transportation system. The approach is to use a cellular automata (CA) microsimulation. CA traffic models divide the transportation network into a finite number of cells. In the current form each cell's length is the average distance between vehicles when traffic is at a complete standstill. A cell may be empty or contain a single vehicle. If it contains a vehicle, the vehicle has an integer velocity between zero and maximum velocity, Vmax=5. The integer velocity represents the number of cells that vehicle moves the next step. The step size is exactly one second, in which case Vmax corresponds to 135 km/hour, or about 84 mph. This step size abets fast computation because the updated vehicle position is computed by integer arithmetic and without multiplication of velocity and time step.

Updating the vehicle's next velocity and position is quite simple. First, we define the number of unoccupied cells ahead of the vehicle as its “gap”. Then, we update the velocity by accelerating to the maximum velocity without running into the vehicle ahead:

$$V(t+1)=\min[V(t)+1,V_{max},gap].$$

But, with probability P, we reduce this tentative velocity by one (without going backwards):

$$V(t+1)=\max[V(t+1)-1,0].$$

Finally, we update the vehicle's position:

$$X(t+1)=X(t)+V(t+1).$$

This rule set is called the Nagel-Schreckenberg model. The random velocity reduction process captures driver behavior such as free-speed driving fluctuations, non-deterministic accelerations, and overreactions when braking. The simple one-lane model has been extended to cover lane changing, passing, merging, and turning behaviors.

The simple model produces dynamics observable in everyday freeway traffic. First, we can display an individual vehicle's movement in space and time as shown in Figure 1. Vehicles moving at constant velocity leave straight-line tracks slanting downward to the right. A stopped vehicle moves in time, but not in space, creating a vertical line. The figure shows the spontaneous formation of well-known traffic shock waves that propagate backward in space.

Emissions Modules

An essential component for TRANSIMS is an emissions model that can give emissions specific to the type of driving being done. In this paper we report results-based on a model developed by investigators at the University of Michigan[4]. The emissions describe a composite vehicle and are based on FTP-revision studies by the US EPA[5]. Currently, we are only estimating emissions from normally operating vehicles with hot catalyts and warm engines. Malfunctioning vehicles, cold starts, and more vehicle types will be addressed when we replace the University of Michigan model with one developed by University of California at Riverside and University of Michigan investigators who are working on a contract for the National Cooperative HIghway Research Program.

Evaporative emissions are not discussed in this paper.

The primary output of the transportation micro-simulation module will be summarized cellular-automata (CA) data. The CA describes the vehicle position in units of cells, velocity in units of cells per second and the acceleration in units of cells per second per second. A typical cell size is 7.5 meters so that the resulting motion, in 16 mph increments, is too coarse to be used directly as input to the emissions module. We are developing an approach to produce realistic, smooth vehicle trajectories that can be used in the emissions module.

The challenge is to provide an adequate representation of actual speeds and accelerations. Since those few vehicles that have sufficient acceleration to produce enriched operation will contribute disproportionally to the total emissions it is important to represent the tails of the acceleration distribution. In order to address this question we examined the three cities data and looked at the frequency distribution of accelerations. Figure 2 reports such a distribution for vehicles with speeds greater than 1 CA cell per second. If we look at the vehicles with higher accelerations we see that a good fit to the curve is obtained with an exponential in the velocity-acceleration product. With this information as a guide we have chosen to consider all accelerations or decelerations in three groups: (1) hard accelerations to represent the ten percent most aggressive accelerations, (2) insignificant accelerations, and (3) hard decelerations.Within the hard acceleration or hard deceleration groups we will pick several points on the conditional acceleration curves to describe different levels of aggressiveness.

With this approach we need to estimate the speed distribution and the probability of a hard acceleration, an insignificant acceleration, and a hard deceleration The most important task is to determine the fraction of the vehicles undergoing hard acceleration because the emissions are more sensitive to hard accelerations than they are to decelerations.

The speed distribution can be estimated by fitting a continuous distribution to the spatial and speed CA populations. We use a constant (f_{ij}) plus a term (h_{ij}) proportional to velocity within the cell and require that the distribution is continuous between velocity cells for a given spatial cell.
In this notation the i index refers to the speed bin and the j index refers to the spatial cell. In this formulation the speed is written as:

$$v = (i-1)\Delta + \delta v,$$

with Δ as the CA speed bin size, 7.5 meters per second and δv the speed relative to the lower limit of the speed bin. The position is given by:

$$x = X_j + \delta x.$$

If the speed remains constant over the next second, the new position is:

$$xn = X_j + \delta x + (i-1)\Delta + \delta v = X_n + \delta xn,$$

which allows us to calculate the new CA speed bin as:

$$k = 1 + \frac{X_n - X_j}{\Delta} = 1 + \frac{\delta x + (i-1)\Delta + \delta v - \delta xn}{\Delta}.$$

This expression allows us to develop inequalities that describe what combinations of δx and δv will permit the vehicle to remain in the same speed bin (k=j) or jump to the next higher speed bin. We can then calculate the total spatial and speed cell populations as:

$$F_{ij} = \frac{\Delta^2}{2} f_{ij} + \frac{\Delta^3}{6} h_{ij} + \frac{\Delta^2}{2} f_{i-1j} + \frac{\Delta^3}{3} h_{i-1j}.$$

Note that with speeds spanning five cells we will CA populations in six speed bins. We use the continuity requirements plus the conditional that the vehicle density goes to zero at the top of the last cell along with the CA population relationships to calculate the velocity distribution parameters f_{ij} and h_{ij}.

The next question is what are the probabilities of a hard acceleration in a given cell? Accelerations arise in two ways: (1) there is ensemble acceleration as for example, vehicles leave a stop or accelerate up an on-ramp and (2) there is individual acceleration as vehicles escape from spontaneous traffic jams. In the latter case, if we look at cell populations averaged over times long compared to the jam formation and dissolution, the cells will display a speed distribution that reflects vehicles slowing down for jams and speeding up on the downstream side of the jams. A logical parameter to capture this type of accelerations is the standard deviation of the speeds. In the case of the bulk accelerations, we need a parameter that reflects changes in the product of the vehicle density (in both space and velocity space) and the product of acceleration and speed. Since we can express acceleration as $a = \frac{\partial v}{\partial x} v$, we need a parameter of the form $v^2 \frac{\partial v}{\partial x}$ or to within a constant $\frac{\partial v^3}{\partial x}$. Specifically, we use the parameter:

$$sp = \frac{\partial}{\partial x}\left(\frac{\int v^3(f + h\delta v)dv}{\int (f + h\delta v)dv}\right).$$

With the parameters chosen, we next have to find the appropriate constants. The approach is to assume that the probability of a hard acceleration is proportional to difference between the chosen parameter and a threshold until a saturation value is reached after which the probability is constant. In order to find the appropriate constants w e began with actual vehicle trajectories from a database developed by the California Air Resource Board[6]. We overlaid a grid on the vehicle's trajectory and deduced equivalent CA positions and velocities. For each actual trajectory, we constructed 400 trajectories slightly offset in time and space to more accurately represent the cell positions expected in real traffic. When we accumulated positions, we weighted the number by the inverse of the total number of all trajectories with the result that the emissions represent those of a single average vehicle.

The trajectories were grouped into 10 sets; three sets of arterials, slow, medium, and fast, and 7 freeway sets ordered by increasing congestion. The most uncongested freeway set had average speeds of about 60 mph while the most congested set had average speeds of about 10 mph. In each case we used only the first 30 seconds of the driving. From the synthetic CA data we collected the fraction of the vehicles in each CA speed bin in each CA cell. We lumped the populations from four spatially adjacent cells for computational efficiency. We fit the cell populations with our continuous distributions and estimated the standard deviations of the velocities and estimated sp for each spatial cell. We then chose thresholds, slopes, and saturation values for both the standard deviations and sp. With the resulting hard acceleration probabilities we obtained the acceleration distribution for each spatial and speed cell and combined that with the speed distribution to provide input to the emission model. We also took the speeds and accelerations from the actual trajectories and compared the resulting emissions to those produced from the synthetic CA data. We used the resulting information to improve our estimates of the fitting constants.

The averages of speeds, CO emissions, NOX emissions, hydrocarbon emissions, and fuel consumption were compared to those from the original trajectories. Figure 3 reports such a comparison for speeds for the fastest freeway (top), a mid-range freeway (middle, set 3), and a very slow freeway (bottom, set 6). The speeds show large differences among the tree sets and the constructed continuous distribution is very close to the actual distribution. The apparent increase of speeds with distance in the slower sets results from slower vehicles disappearing from the set after 30 seconds without reaching the more distant CA cells. Figure 4 reports the comparison for NOX emissions for the aforementioned freeway sets. Once again the constructed distribution is quite close to the actual distribution. However, there is very little difference in NOX emissions among the three sets except in the downstream portions of the two lower plots where many of the vehicles have disappeared. Figure 5 shows a similar plot for hydrocarbon emissions. In this case there are some differences relating to the starts of the trajectories associated with the artificialities of the trajectories. Figure 6 reports a similar plot for CO emissions. In this plot, the slowest set has somewhat lower emissions as opposed to the other two.

Figure 7 reports the speed comparisons for the fast (top), medium (middle), and slow (bottom) arterials. Once again, the fits are quite good. In Figure 8 we have the plots for NOX emissions, that show a large hump associated with some of the vehicles starting out from a red light while others passed through on green. There is not much difference between the plots, except that the high emission hump is more extended for the higher speed arterial. Generally the constructed model does very well, although there some spurious humps that might suggest a need for better smoothing. Figure 9 reports hydrocarbon emissions and Figure 10 reports CO emissions.

Overall the model shows good agreement with the emissions estimated for the actual trajectories. Furthermore, there is relatively little difference in emissions between the various conditions. The most important emissions changes occur when there are vehicles accelerating out from a stop. The acceleration of vehicles up to speed after spontaneous traffic jams also plays a significant role.

Currently, the modal emission model takes the form of an array that translates speeds and accelerations into emissions of composite vehicles. In the future, it may be useful to consider the history effects on emissions. In such an instance we can use our estimated acceleration probabilities to construct trajectories for different levels of aggressiveness and process the trajectories with an emission module that takes into account the history effects on emissions.

SUMMARY

The TRANSIMS environmental module uses inputs from the TRANSIMS planner and traffic microsimulation. An examination of the consequences of coarse-graining actual trajectories into CA bins shows that a good representation of actual emissions can be obtained. The representation was good even though the data set includes circumstances under which enrichment can occur. Enrichment conditions pose a challenge, because the emissions can be very sensitive to magnitude and frequency of accelerations. Rarely do we have data that permits an estimation of the high-end tail of the acceleration distribution.

The major elements responsible for emissions are organized accelerations such as those that occur when leaving a stop and incoherent accelerations as individual vehicles resume speed after leaving a spontaneous traffic jam. Speed alone does not appear to be a major factor in NOX emissions, when emissions are compared on a per vehicle entering the link and per unit space basis.

ACKNOWLEDGMENTS

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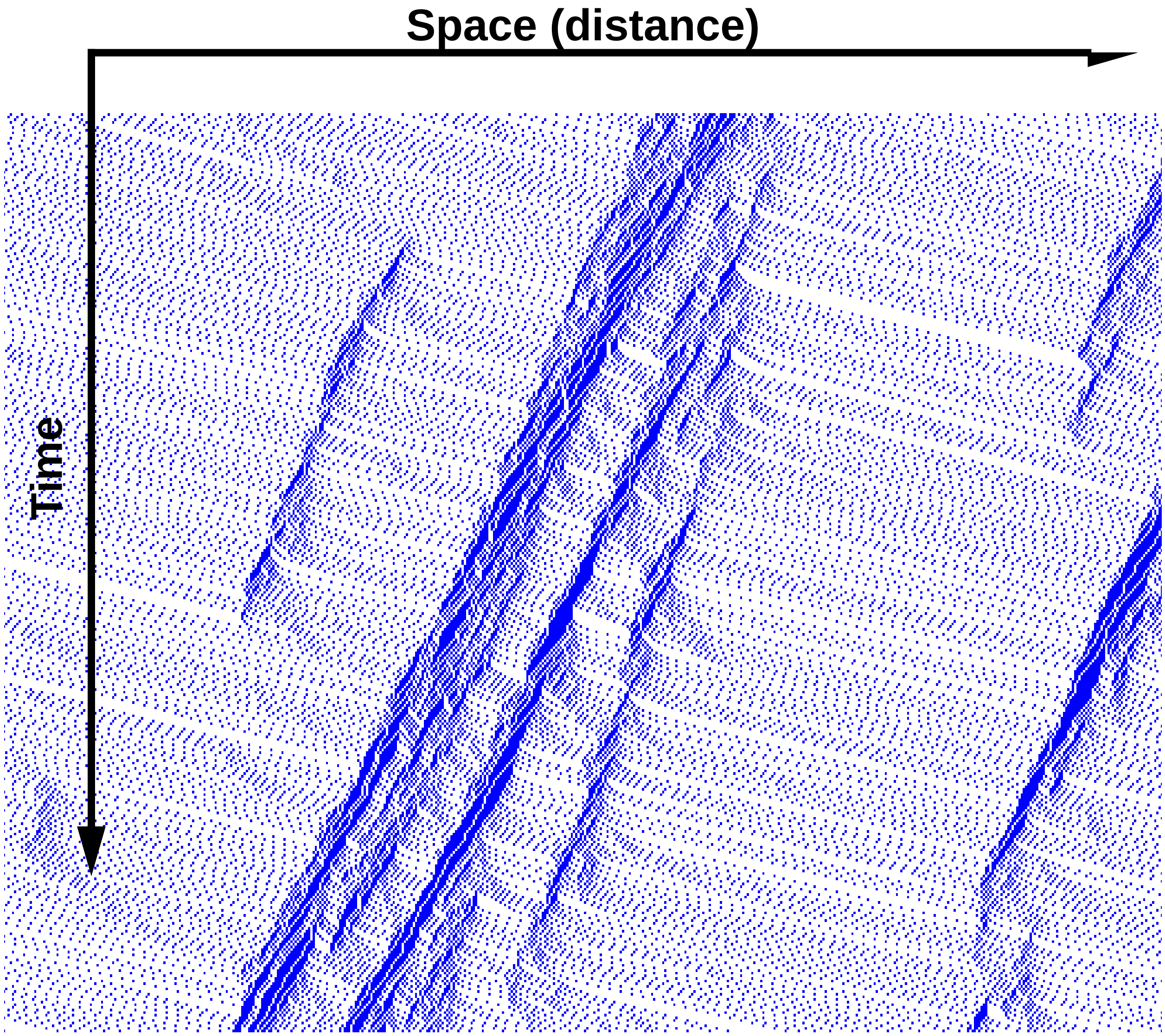

Figure 1. Waterfall plot for traffic produced by the cellular automata model showing time and space trajectories influenced by spontaneous formation of traffic jams. Dots showing a constant slope represent vehicles traveling at a constant velocity, while heavy, backward-sloping smears show the accumulation of vehicles in a traffic jam.

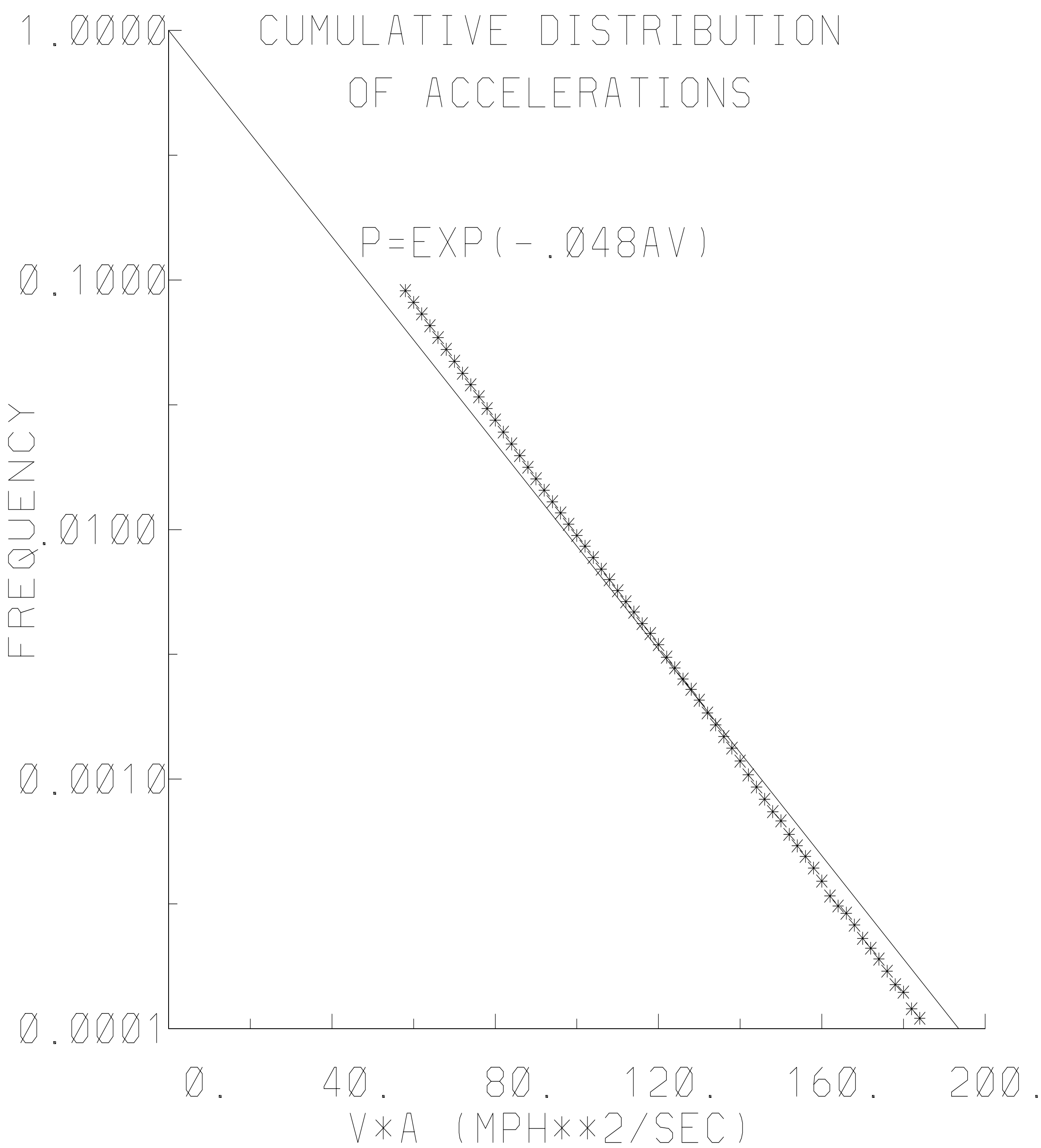

Figure 2. The cumulative distribution of accelerations for vehicles in Baltimore with speeds over 7.5 meters per second and with positive accelerations.

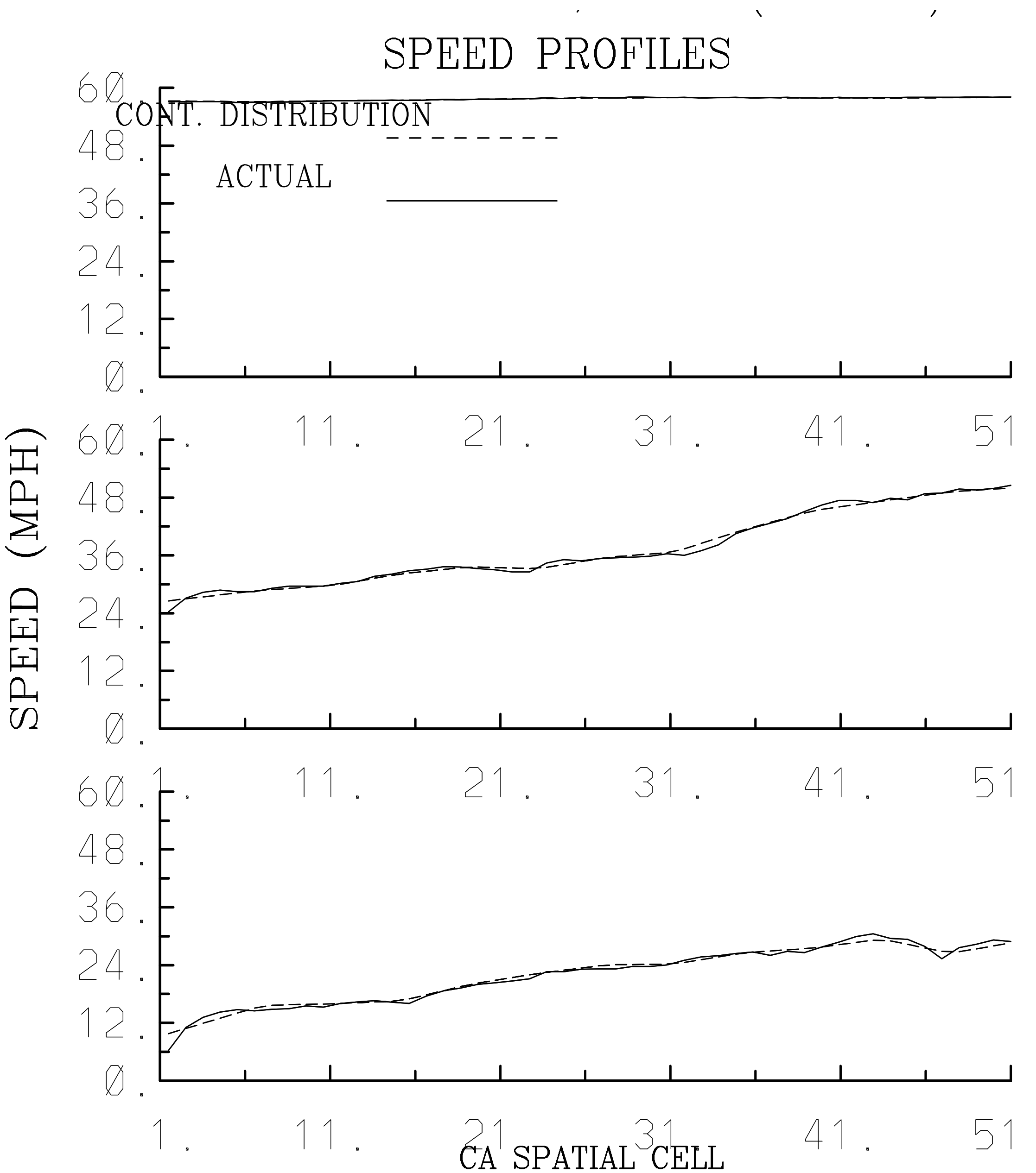

Figure 3. A comparison of average speeds between the estimated distribution and the actual distribution for the fastest freeway (set 1, top), a medium-speed freeway (set 3, middle), and a very-slow freeway (set 6, bottom).

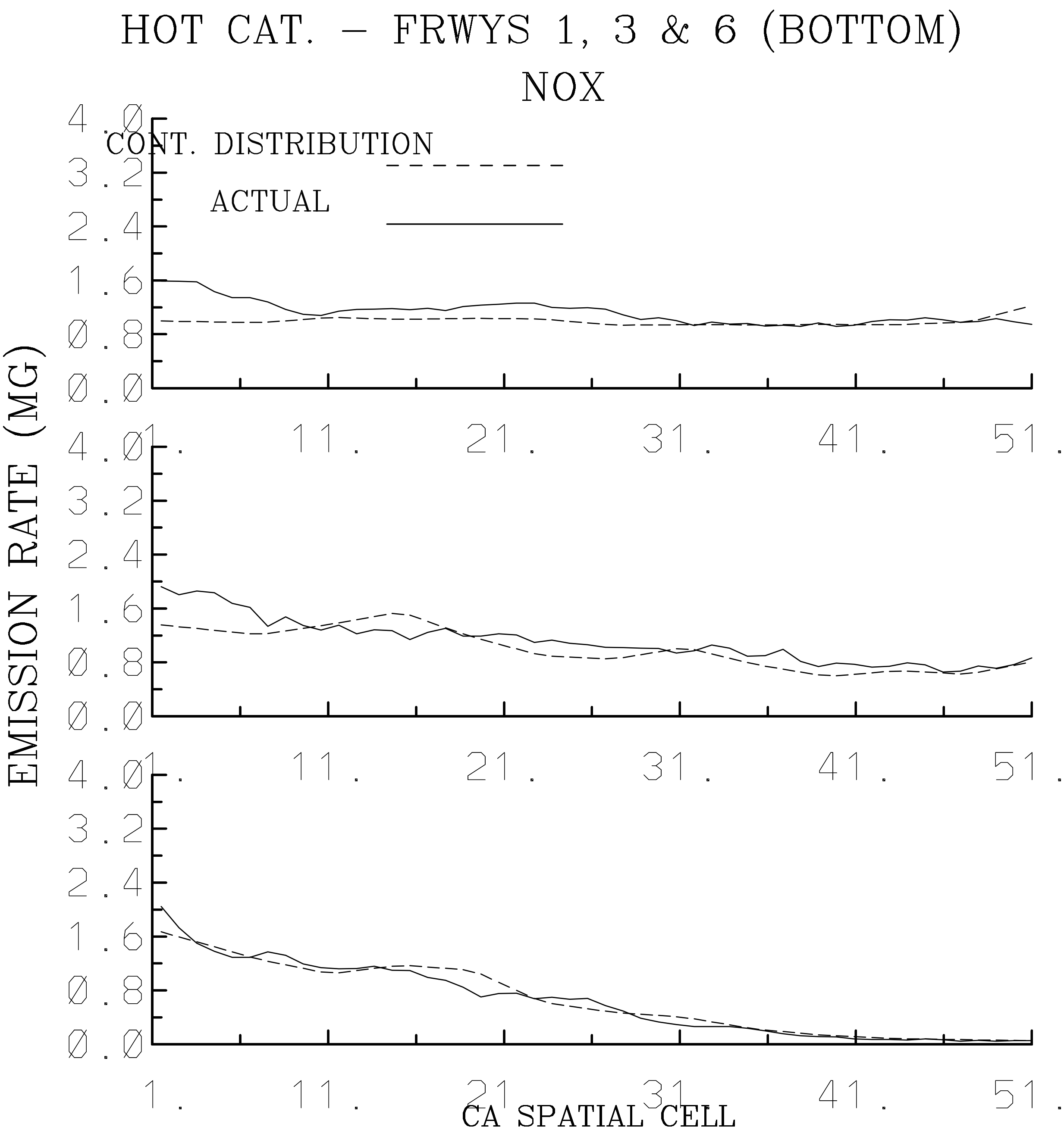

Figure 4. A comparison of average NOX emissions between the estimated distribution and the actual distribution for the fastest freeway (set 1, top), a medium-speed freeway (set 3, middle), and a very-slow freeway (set 6, bottom). The emissions are in milligrams per 7.5 meter cell.

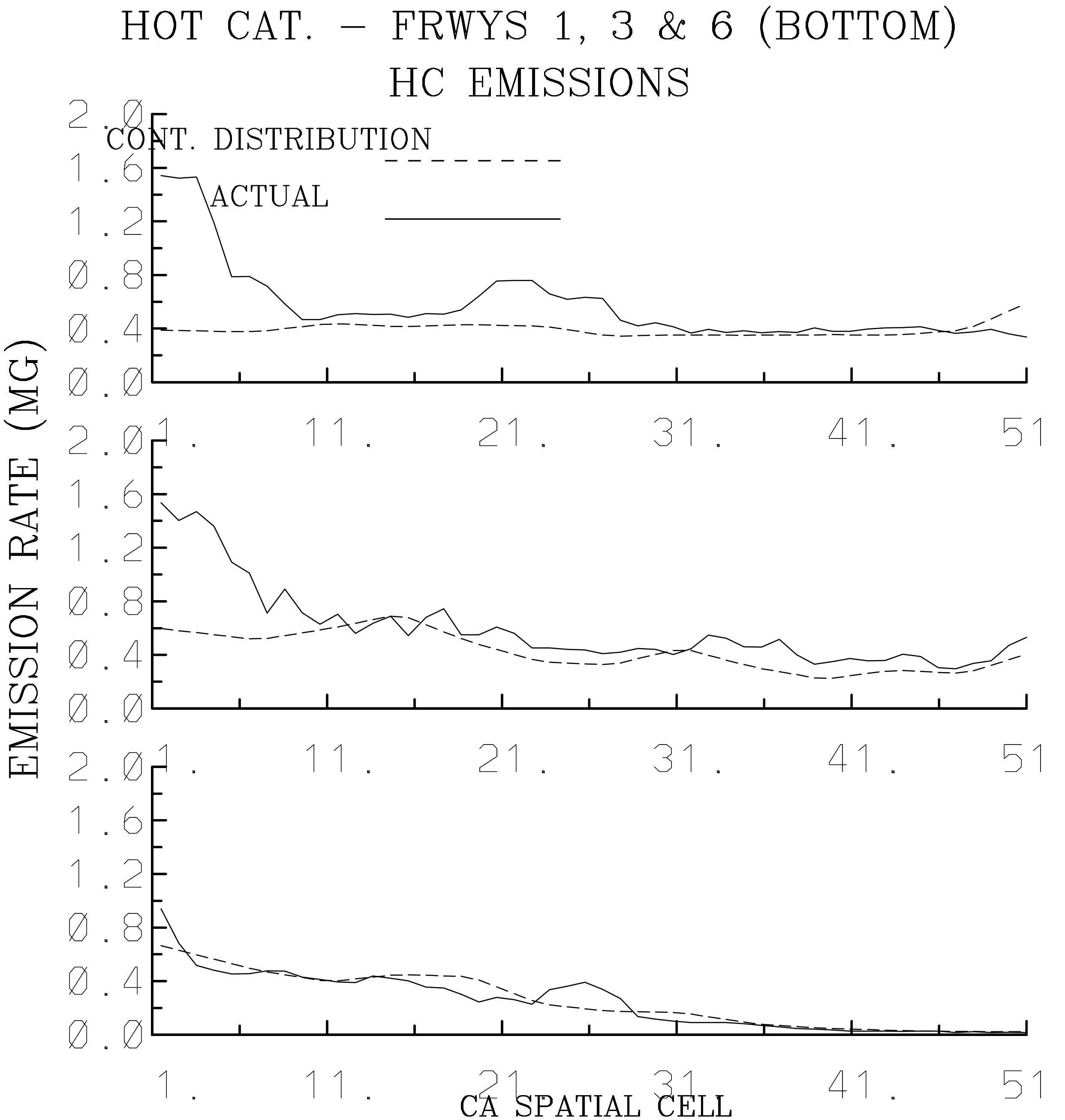

Figure 5. A comparison of average hydrocarbon emissions between the estimated distribution and the actual distribution for the fastest freeway (set 1, top), a medium-speed freeway (set 3, middle), and a very-slow freeway (set 6, bottom). The emissions are in milligrams per 7.5 meter cell.

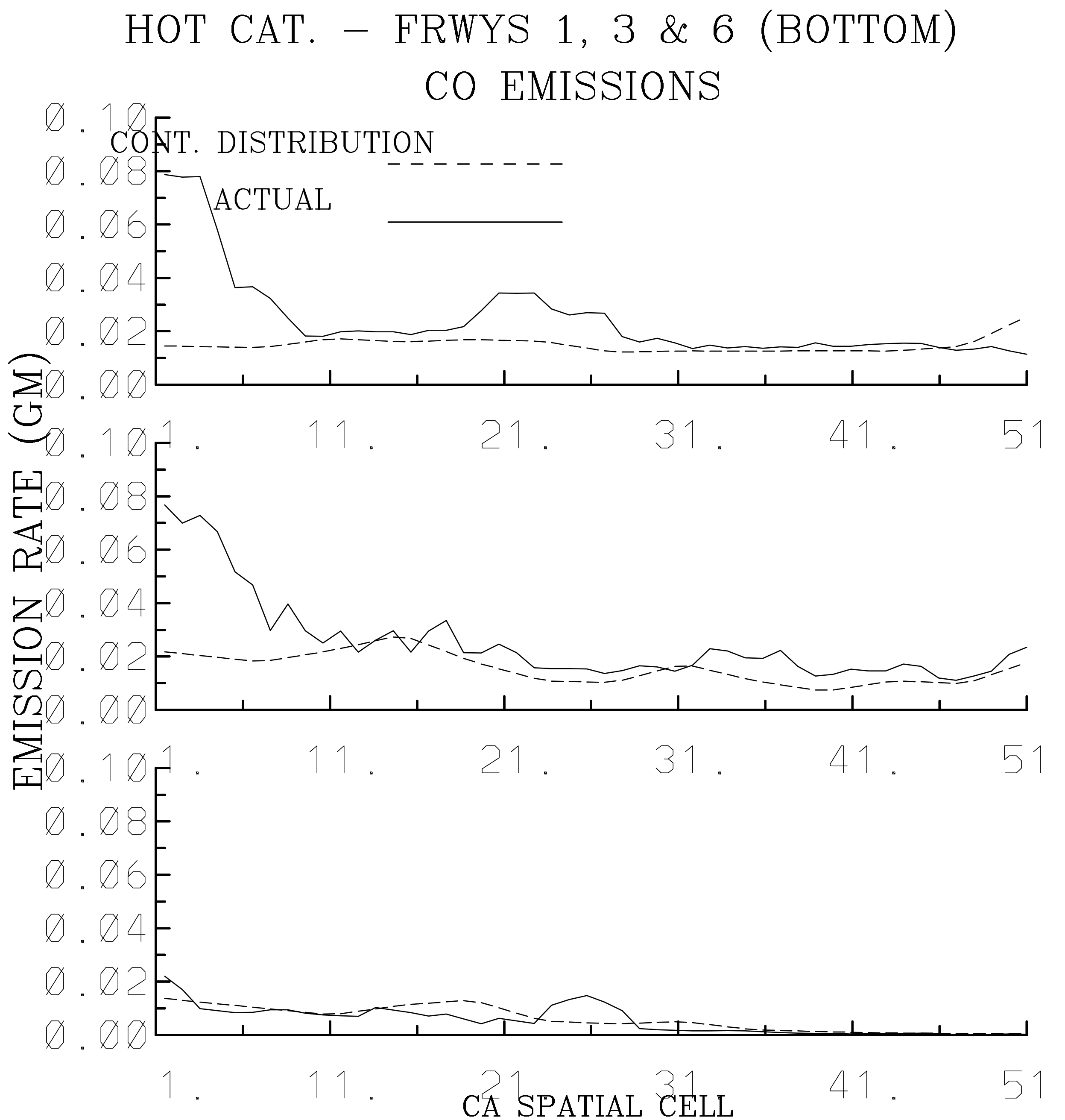

Figure 6. A comparison of average carbon-monoxide emissions between the estimated distribution and the actual distribution for the fastest freeway (set 1, top), a medium-speed freeway (set 3, middle), and a very-slow freeway (set 6, bottom). The emissions are in grams per 7.5 meter cell.

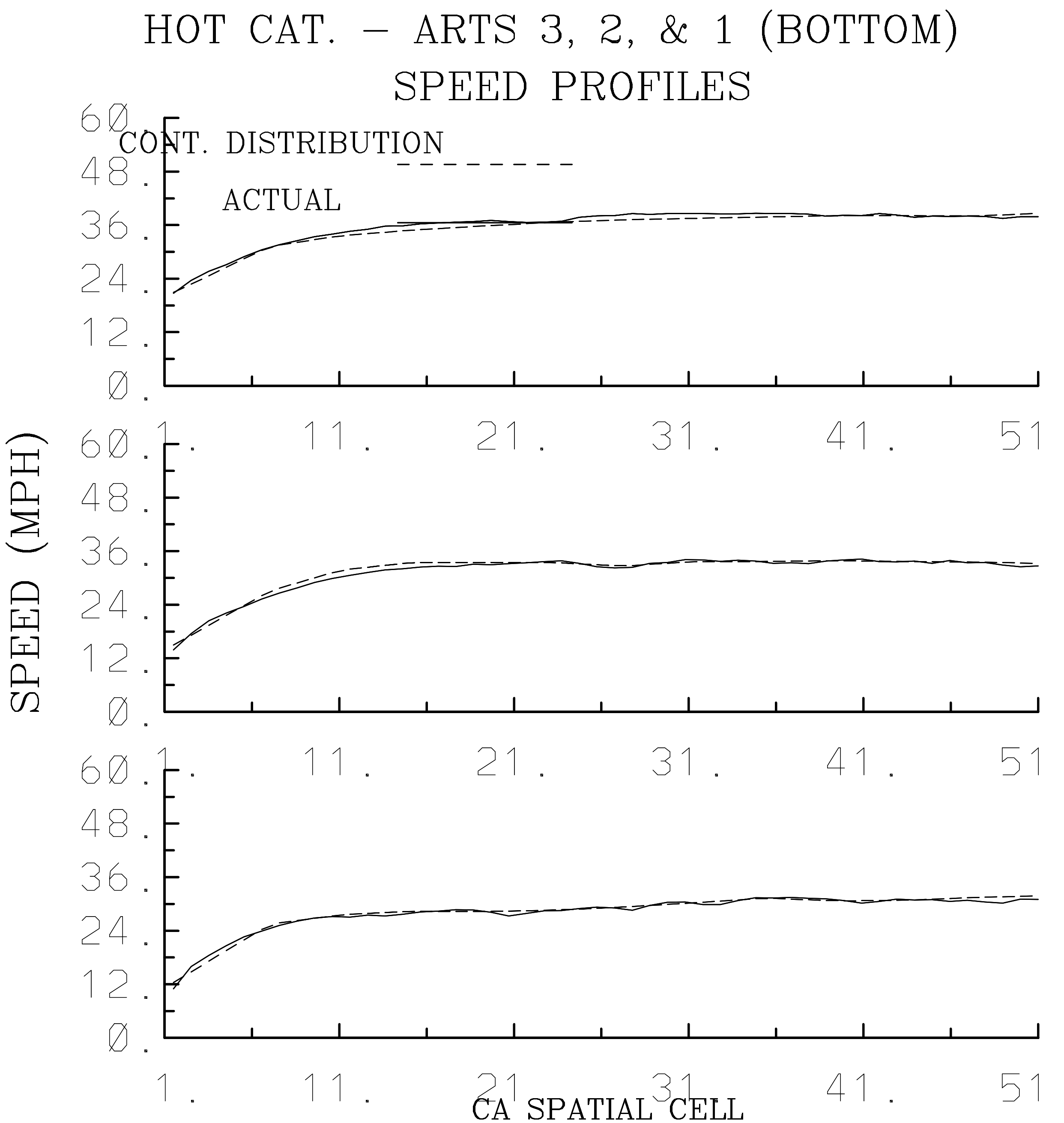

Figure 7. A comparison of average speeds between the estimated distribution and the actual distribution for the fastest arterial (set 3, top), a medium-speed arterial (set 2, middle), and a -slow arterial (set 1, bottom).

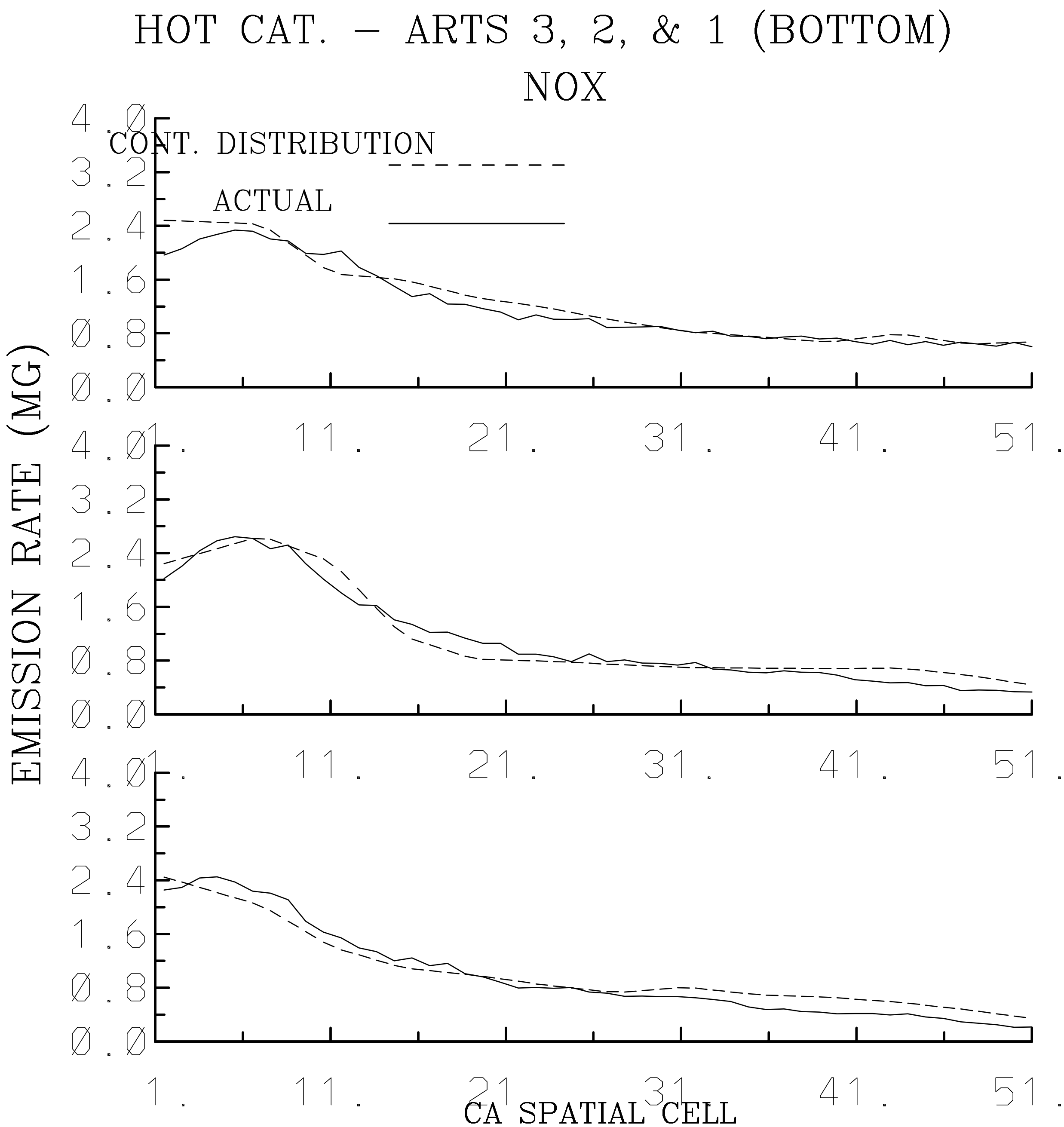

Figure 8. A comparison of average NOX emissions between the estimated distribution and the actual distribution for the fastest arterial (set 3, top), a medium-speed arterial (set 2, middle), and a slow arterial (set 1, bottom). The emissions are in milligrams per 7.5 meter cell.

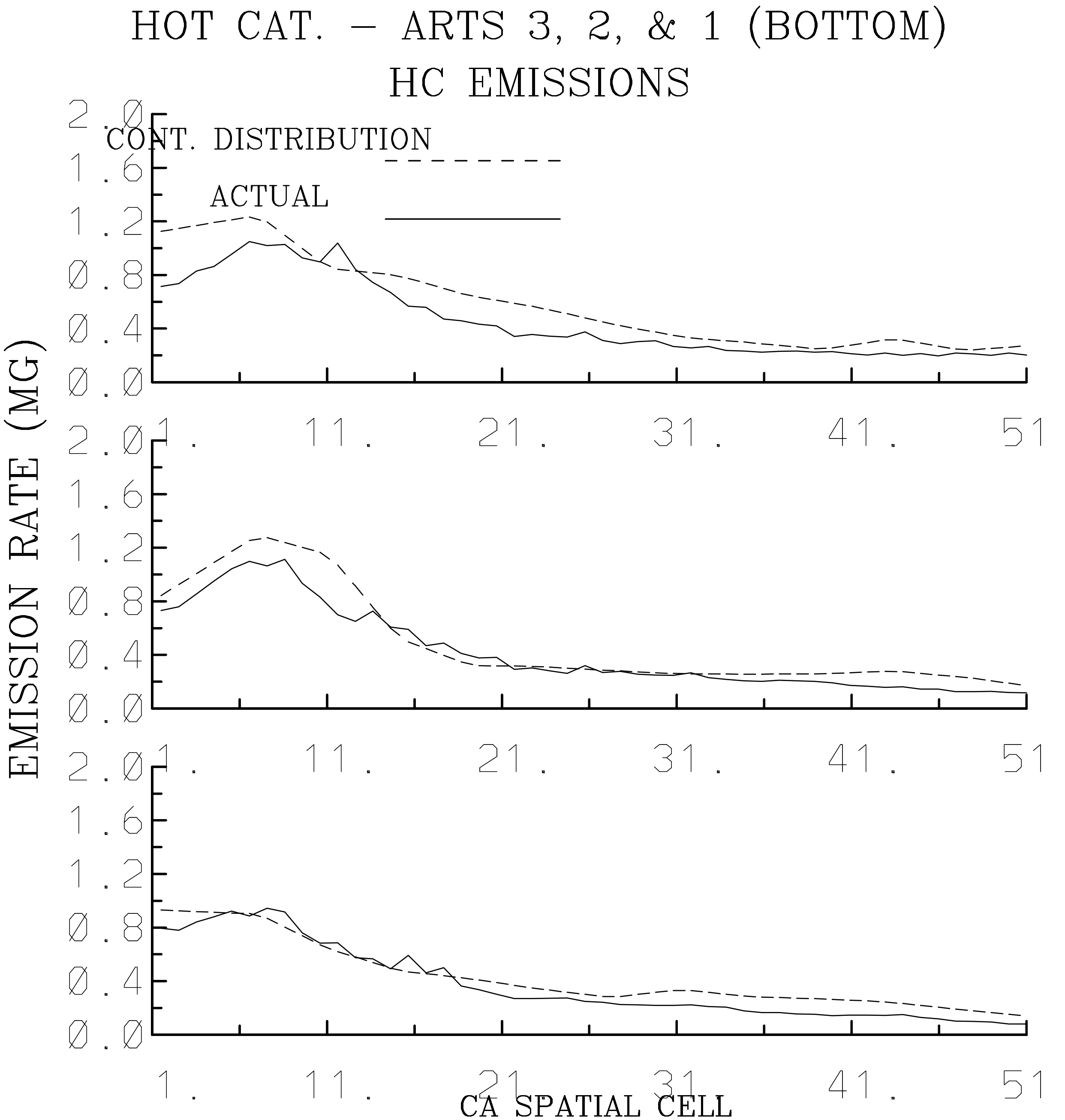

Figure 9. A comparison of average hydrocarbon emissions between the estimated distribution and the actual distribution for the fastest arterial (set 3, top), a medium-speed arterial (set 2, middle), and a slow arterial (set 1, bottom). The emissions are in milligrams per 7.5 meter cell.

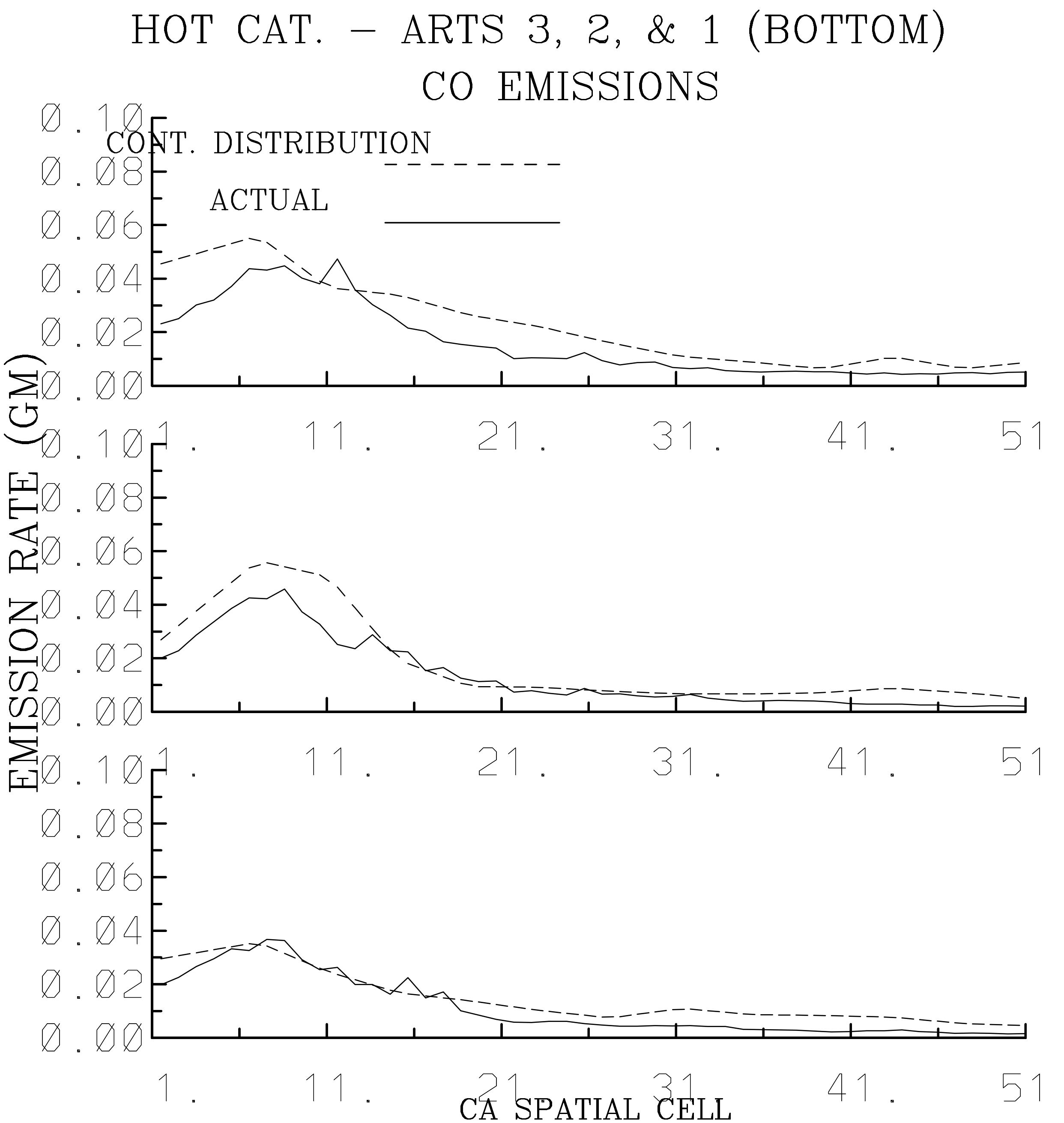

Figure 10. A comparison of average carbon-monoxide emissions between the estimated distribution and the actual distribution for the fastest arterial (set 3, top), a medium-speed arterial (set 2, middle), and a slow arterial (set 1, bottom). The emissions are in grams per 7.5 meter cell